L Number	Hits	Search Text	DB	Time stamp
1	52	brain with model and node and back with propagation	USPAT; US-PGPUB	2003/10/10 16:36
2	5137	back with propagation	USPAT; US-PGPUB	2003/10/10 16:36
3	21	back with propagation and brain with model and node and sigmoid	USPAT; US-PGPUB	2003/10/10 16:37
4	0	back with propagation and brain with model and node and sigmoid with curve	USPAT; US-PGPUB	2003/10/10 16:37
5	12	back with propagation and brain with model and node and sigmoid with function	USPAT; US-PGPUB	2003/10/10 16:37
6	3	back with propagation and brain with model and node and sigmoid with function and (buz$3 or flash$3)	USPAT; US-PGPUB	2003/10/10 16:41
7	0	back with propagation and brain with model and node and sigmoid with function and (buz$3 with flash$3)	USPAT; US-PGPUB	2003/10/10 16:41
8	0	back with propagation and brain with model and node and sigmoid and function and (buz$3 with flash$3)	USPAT; US-PGPUB	2003/10/10 16:42
9	0	back and propagation and brain with model and node and sigmoid and function and (buz$3 with flash$3)	USPAT; US-PGPUB	2003/10/10 16:42
10	10	back and propagation and brain with model and node and sigmoid and function and (buz$3 or flash$3)	USPAT; US-PGPUB	2003/10/10 16:42
11	6	back$4 with propagation and brain with model and node and sigmoid and function and (buz$3 or flash$3)	USPAT; US-PGPUB	2003/10/10 16:45
12	0	spatial with target and algorithm adj model with (neural with network)	USPAT; US-PGPUB	2003/10/10 16:55
13	10	spatial with target and algorithm and model with (neural with network)	USPAT; US-PGPUB	2003/10/10 16:58
14	4	spatial with target and algorithm and model with (neural with network) and back with(scatter or propagation)	USPAT; US-PGPUB	2003/10/10 17:03
15	1	spatial with target and algorithm and model with (neural with network) and back with(scatter or propagation) and sigmoid with curve	USPAT; US-PGPUB	2003/10/10 17:03
16	2	spatial with target and algorithm and model with (neural with network) and back with(scatter or propagation) and sigmoid with function	USPAT; US-PGPUB	2003/10/10 17:03

US-PAT-NO: 6084981

DOCUMENT-IDENTIFIER: US 6084981 A

TITLE: Image processing apparatus for performing image converting process by neural network

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Abstract Text - ABTX (1):

An image processing apparatus using a **neural network** having: an image supplying unit for supplying spatiotemporal data of a predetermined region including a target pixel of an image; and a **neural network** formed by coupling a plurality of artificial neuron **models** so as to have at least an input layer, a hidden layer, and an output layer, wherein in the output layer, an input/output converting process is executed by a linear function and data corresponding to a target pixel is outputted from the output layer.

Brief Summary Text - BSTX (5):

(1) An example in which a neural network is used to eliminate Gaussian random noise mixed into a 2-dimensional image has been reported. [Kaoru Arakawa and Hiroshi Harashima, "Designing of Layered-Neural Non-linear Filters using **Back Propagation Algorithm**", the papers of The Institute of Electronics Information and Communication Engineers of Japan, Vol. J74-A, No. 3, pages 421-429, 1991]. According to the above paper, an .epsilon. filter is realized by a neural network.

Brief Summary Text - BSTX (13):

To accomplish the above object, according to the present invention, there is provided an image processing apparatus comprising: an original image supplying unit for outputting image data of a processing target; an image conversion processing unit for inputting the image data from the original image supplying unit and performing an image converting process; and a display unit for inputting and displaying the image information which was subjected to the image converting process by the image conversion processing unit and was outputted,

wherein the image conversion processing unit is constructed by a **n ural n twork**
formed in a manner such that a **network** is constructed by coupling artificial neuron **m dels** so as to have a layer structure of an input layer, a hidden layer, and an output layer and spatiotemporal data of a predetermined region including at least a target pixel is inputted from the original image supplying unit and the

Detailed Description Text - DETX (5):
In the invention, the image conversion processing unit 2 is constructed by a neural network 4 as shown in FIG. 2. The neural network 4 receives the spatiotemporal data of a predetermined region including at least a target pixel from the original image supplying unit 1 and executes an image converting process and outputs the data corresponding to the target pixel. The **neural network** 4 constructs a **network** by coupling artificial neuron **models** 5 so as to have a layer structure of an input layer 21, a hidden layer 22, and an output layer 23 and is constructed by using a linear function as an input/output function of the output layer at the final stage.

Detailed Description Text - DETX (6):
FIG. 3 is an explanatory diagram showing the artificial neuron **model** 5 constructing the **neural network** 4. As shown in the diagram, the artificial neuron model (hereinafter, simply referred to as a "neuron model") 5 is a model of multi-inputs and one output which simulates the operation of a neuron of an organism. An output O.sub.j is determined by the sum of products of inputs I.sub.i (I.sub.I to I.sub.n) and weight coefficients W.sub.ji (W.sub.jl to W.sub.jn). Namely, the output O.sub.j is expressed as shown by the following equation (1) by using an input/output function f(x). ##EQU1## where, .theta..sub.j : offset of the input/output function corresponding to a threshold value

Detailed Description Text - DETX (11):
FIG. 2 mentioned above is an explanatory diagram showing a structure of the neural network 4 constructed as a network by coupling so as to have a layer structure. As shown in FIG. 2, the **neural network** 4 is constructed so as to realize functions of a signal processing and an information processing by constructing a **network** by using a number of neuron **models** 5 mentioned above and
coupling them so as to have a layer structure of the input layer 21, hidden layer 22, and output layer 23. In FIG. 2, reference numeral 6 denotes branches

for coupling the input layer 21 and hidden layer 22. Each neuron model 5 of the input layer 21 is coupled to all of the neuron models 5 of the hidden layer 22. Reference numeral 7 denotes branches for connecting the hidden layer 22 and output layer 23. Each neuron model 5 of the hidden layer 22 is coupled with all of the neuron models 5 of the output layer 23. The neural network 4 converts input information 8 which is supplied to the input layer 21 and generates as output information 9 from the output layer 23.

Detailed Description Text - DETX (18):

FIG. 7 is an explanatory diagram showing the input information 8 and output information 9 regarding a target pixel of the neural network 4. As shown in the diagram, a plurality of image data arranged on a time base is inputted to frame memories 20. The input information 8 to the neural network 4 is spatiotemporal data 14 obtained by extracting the data in a predetermined region including a target pixel 12 on an original image 11 and a plurality of pixels 13 near the target pixel 12 in the direction of a time base t only for a predetermined time by a controller 19. The predetermined region has an optional form for each frame. The pixel data of the optional form which are stored in the frame memory 20 are inputted into each of the neuron models 5 of the input layer 21. For example, when nine pixels are present, the pixel data are inputted into nine neuron models 5, when five pixels are present, the pixel data are inputted into five neuron models 5, and when three pixels are present, the pixel data are inputted into three neuron models 5, as shown in FIG. 7. In the example of FIG. 7, the spatiotemporal data 14 comprises data of 23 (=9+5+5+3+1) pixels. The values of the above pixels are, for example, normalized and inputted to the neural network 4. In the **neural network** 4, the weight coefficients and offset value of the neuron **model** are set by a learning operation, which will be explained hereinlater, in a manner such that in the case where the original image 11 accompanied with a motion and noise is inputted, noise in which a correlation is time spatially small and a motion which time spatially has a regularity can be distinguished. Therefore, in an operating mode, it is possible to cope with a moving image with low noise and without being accompanied with a blur by the motion. In the neural network 4, consequently, the image data as input information 8 is converted and is outputted as pixel data 15 corresponding to the target pixel 12 on the original image 11. By moving the target pixel 12 on the original image 11 in, for example, a raster scanning manner, the pixel data 15 corresponding to each target pixel 12 is sequentially outputted and the image converting process of the whole image is executed. A conversion image 16 is formed by the raster scanning-like image formation of the pixel data 15 which is sequentially outputted and is outputted.

Detailed Description Text - DETX (75):
In the image processing apparatus of the invention, the learning operation of the neural network 4 is executed on the **algorithm** as shown in FIG. 10 on the basis of the teach signals 10 which are given by the operator. Although the neural network 4 of three layers has been shown here as an example, by increasing the number of hidden layers, a neural network 4 of four or more layers can be constructed. As a learning **algorithm** in such a case, it is sufficient that the error amount .delta. is back propagated so as to obtain .delta..sub.2 by using .delta..sub.3 and a correction amount of each neuron model. It is possible to cope with image information including more complicated conversion. The image data converted by the neural network 4 is converted into a proper density scale (not shown) and is inputted to the display unit 3 shown in FIG. 1 and is displayed.

Detailed Description Text - DETX (78):
As shown in FIG. 12B, with respect to the compression in the **spatial** direction in the original image 11, the number of pixels is increased as the pixel position is away from the **target** pixel 12, thereby averaging the image data. Namely, although the image data of a pixel p adjacent to the target pixel 12 is held as it is, in a portion q which is in contact with the pixel p, the image data of two pixels is averaged. By the above averaging processes, the number of data which is inputted to the neural network 4 is reduced and the complicated image converting processes each of which needs a long time or a wide region can be executed at a high speed.

Detailed Description Text - DETX (82):
supplying unit 71 by the ideal apparatus system and doesn't include the noise or character is supplied to the neural network 4 and the learning operation is executed by the **algorithm** shown in FIG. 10 mentioned above. Upon
learning, the noise or character is detected as .SIGMA..vertline.T-O.sub.3 .vertline. in FIG. 10. A conversion **model** to the ideal apparatus system which doesn't include the noise or character has automatically been constructed from the target apparatus system including the noise or character for the **neural network** 4 after completion of the learning. In the operating mode, the noise or character can be effectively eliminated with respect to the inputted original image.

Detailed Description Text - DETX (83):

For example, a case where an X-ray photographing apparatus for photographing by X-rays of a low dose is set to a target system will now be described. An X-ray image photographed by the X-rays of a low dose is supplied from the original image supplying unit 1 to the neural network 4. An X-ray image with small X-ray quantum noise which was photographed by X-rays of a high dose or an X-ray image obtained by averaging a plurality of X-ray images of a low dose on a pixel unit basis is supplied from the teach image supplying unit 71 to the neural network 4. Thus, the neural network 4 detects an X-ray quantum noise component as .SIGMA..vertline.T-O.sub.3 .vertline. in FIG. 10 and executes the learning operation so as to reduce the X-ray quantum noise. A conversion **model** from the X-ray image of a low dose to the X-ray image of a high dose is automatically constructed in the **neural network** 4 after completion of the learning. That is, the image converting process in which the X-ray quantum noise are reduced is realized. Even in the case where the X-ray image of a low dose is inputted, the same X-ray image as that obtained as if it was photographed by X-rays of a high dose is outputted.

Detailed Description Text - DETX (84):

A case of eliminating noise of an X-ray image in association with a motion will now be described as another example. The X-ray image of a low dose accompanied with the motion is supplied from the original image supplying unit 1 to the neural network 4. The X-ray image of a high dose accompanied with the motion is supplied from the teach image supplying unit 71 to the neural network 4. The neural network 4 detects the noise component of the X-ray image accompanied with the motion as .SIGMA..vertline.T-O.sub.3 .vertline. in FIG. 10 and performs the learning operation so as to reduce the noise component. A conversion **model** in which the noise are reduced without being accompanied with a blur due to a motion is automatically constructed in the **neural network** 4 after completion of the learning. An image in which the noise are reduced without being accompanied with a blur due to the motion is outputted.

Detailed Description Text - DETX (86):

According to the invention as mentioned above, the image data which is inputted by a target problem and the image data serving as a teacher are properly supplied from the original image supplying unit 1 and teach image supplying unit 71 to the **neural network** 4 and the **neural network** 4 is allowed to execute the learning operation, so that its conversion **model** is

automatically constructed in the **n ural network** 4. An accurate image having a large transfer information amount can be provided.

Claims Text - CLTX (5):
wherein said original image supplying unit includes means for outputting spatiotemporal data of a predetermined region including a **target** pixel of an image, the spatiotemporal data including first **spatial** data, acquired at a first time, in which the predetermined region has a first size, and second **spatial** data, acquired at a second time prior to the first time, in which the predetermined region has a second size smaller than the first size; and

Claims Text - CLTX (7):
a **neural network** formed by mutually connecting a plurality of artificial neuron **models** so as to have a layer structure of at least an input layer, a hidden layer, and an output layer, and

Claims Text - CLTX (20):
wherein said original image supplying unit includes means for outputting spatiotemporal data of a predetermined region including a **target** pixel of an image, the spatiotemporal data including first **spatial** data, acquired at a first time, in which the predetermined region has a first size, and second **spatial** data, acquired at a second time prior to the first time, in which the predetermined region has a second size different than the first size;

Claims Text - CLTX (23):
converting means for outputting information corresponding to said **target** pixel on a basis of the first **spatial** data and the second **spatial** data, and

Claims Text - CLTX (39):
a **neural network** formed by mutually connecting a plurality of artificial neuron **models** so as to have a layer structure of at least an input layer, a hidden layer, and an output layer, and

Claims Text - CLTX (51):
inputting spatiotemporal data of a predetermined region including a **target** pixel of an image to a **neural network** formed by mutually connecting a plurality of artificial neuron **models** so as to have a layer structure of at least an

input layer, a hidden layer, and an output layer, the spatiotemporal data including first **spatial** data, acquired at a first time, in which the predetermined region has a first size, and second **spatial** data, acquired at a second time prior to the first time, in which the predetermined region has a second size smaller than the first size; and

Claims Text - CLTX (61):
inputting spatiotemporal data of a predetermined region including a target pixel of an image to a **neural network** formed by mutually connecting a plurality of artificial neuron **models** so as to have a layer structure of at least an input layer, a hidden layer, and an output layer;

Claims Text - CLTX (72):
inputting spatiotemporal data of a predetermined region including a **target** pixel of an image to a **neural network** formed by mutually connecting a plurality of artificial neuron **models** so as to have a layer structure of at least an input layer, a hidden layer, and an output layer, the spatiotemporal data including first **spatial** data, acquired at a first time, in which the predetermined region has a first size, and second **spatial** data, acquired at a second time prior to the first time, in which the predetermined region has a second size different than the first size;

Other Reference Publication - OREF (1):
Design of Layered--Neural Nonlinear Fitters Using Back-Propugation **Algorithm**, Arakawa et al 1991 p. 421-429.

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1	52	brain with model and node and back with propagation	USPAT; US-PGPUB	2003/10/10 16:36
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15	1	spatial with target and algorithm and model with (neural with network) and back with(scatter or propagation) and sigmoid with curve	USPAT; US-PGPUB	2003/10/10 17:03
16	2	spatial with target and algorithm and model with (neural with network) and back with(scatter or propagation) and sigmoid with function	USPAT; US-PGPUB	2003/10/10 17:03

	U	1	Document ID	Issu Dat	Pages	Title	Current OR
1	☐	☐	US 6581048 B1	20030617	100	3-brain architecture for an intelligent decision and control system	706/23
2	☐	☐	US 6169981 B1	20010102	101	3-brain architecture for an intelligent decision and control system	706/23
3	☐	☐	US 5687291 A	19971111	30	Method and apparatus for estimating a cognitive decision made in response to a known stimulus from the corresponding single-event evoked cerebral potential	706/10

	Current XRef	R tri val Classif	Inv ntor	S	C	P	2	3	4	5
1	250/369; 706/16		Werbos, Paul J.	☒	☐	☐	☐	☐	☐	☐
2	706/15; 706/16; 706/26; 706/27		Werbos, Paul J.	☒	☐	☐	☐	☐	☐	☐
3	600/544; 600/545; 706/16; 706/45; 706/52		Smyth, Christopher C.	☒	☐	☐	☐	☐	☐	☐

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1	US 6581048	☐
2	US 6169981	☐
3	US 5687291	☐

	U	1	Document ID	Issue Dat	Pages	Titl	Current OR
1	☒	☐	US 6581048 B1	20030617	100	3-brain architecture for an intelligent decision and control system	706/23
2	☒	☐	US 6397201 B1	20020528	34	E-cell (equivalent cell) and the basic circuit modules of e-circuits: e-cell pair totem, the basic memory circuit and association extension	706/33
3	☒	☐	US 6169981 B1	20010102	101	3-brain architecture for an intelligent decision and control system	706/23
4	☒	☐	US 5687291 A	19971111	30	Method and apparatus for estimating a cognitive decision made in response to a known stimulus from the corresponding single-event evoked cerebral potential	706/10
5	☒	☐	US 5167008 A	19921124	55	Digital circuitry for approximating sigmoidal response in a neural network layer	706/43
6	☒	☐	US 5115492 A	19920519	64	Digital correlators incorporating analog neural network structures operated on a bit-sliced basis	706/34

	Current XRef	Retrieval Classif	Inv ntor	S	C	P	2	3	4	5
1	250/369; 706/16		Werbos, Paul J.	☐	☐	☐	☐	☐	☐	☐
2	706/26; 706/40; 706/42		Arathorn, David W.	☐	☐	☐	☐	☐	☐	☐
3	706/15; 706/16; 706/26; 706/27		Werbos, Paul J.	☐	☐	☐	☐	☐	☐	☐
4	600/544; 600/545; 706/16; 706/45; 706/52		Smyth, Christopher C.	☐	☐	☐	☐	☐	☐	☐
5	706/34; 708/201; 708/3		Engeler, William E.	☐	☐	☐	☐	☐	☐	☐
6	706/31; 708/3		Engeler, William E.	☐	☐	☐	☐	☐	☐	☐

	Image Doc. Displayed	PT
1	US 6581048	☐
2	US 6397201	☐
3	US 6169981	☐
4	US 5687291	☐
5	US 5167008	☐
6	US 5115492	☐

	U	1	Document ID	Issue Date	Pag s	Title	Current OR
1	☐	☐	US 20030167148 A1	20030904	17	Method for determination of spatial target probability using a model of multisensory processing by the brain	702/181
2	☐	☐	US 6198843 B1	20010306	22	Method and apparatus for color gamut mapping	382/167
3	☐	☐	US 6173275 B1	20010109	31	Representation and retrieval of images using context vectors derived from image information elements	706/14
4	☐	☐	US 6092058 A	20000718	23	Automatic aiding of human cognitive functions with computerized displays	706/10
5	☐	☐	US 6084981 A	20000704	19	Image processing apparatus for performing image converting process by neural	382/157
6	☐	☐	US 5465221 A	19951107	33	Automated process planning for quality control inspection	702/83
7	☐	☐	US 5107442 A	19920421	10	Adaptive neural network image processing system	706/20
8	☐	☐	US 5075871 A	19911224	10	Variable gain neural network image processing system	706/25
9	☐	☐	US 4941122 A	19900710	8	Neural network image processing system	708/801
10	☐	☐	US 4802103 A	19890131	50	Brain learning and recognition emulation circuitry and method of recognizing events	706/38

	Curr nt XRef	Retrieval Classif	Invent r	S	C	P	2	3	4	5
1			Anastasio, Thomas J. et al.	☒	☐	☐	☐	☐	☐	☐
2	358/518		Nakauchi, Shigeki et al.	☒	☐	☐	☐	☐	☐	☐
3	382/190; 382/195; 382/224; 382/225; 706/12; 706/934		Caid, William R. et al.	☒	☐	☐	☐	☐	☐	☐
4	600/554; 706/15; 706/16		Smyth, Christopher C.	☒	☐	☐	☐	☐	☐	☐
5	382/158; 706/20		Horiba, Isao et al.	☒	☐	☐	☐	☐	☐	☐
6	700/160; 700/173; 700/182; 706/904		Merat, Francis L. et al.	☒	☐	☐	☐	☐	☐	☐
7	382/157; 382/158; 703/11; 706/31		Weideman, William E.	☒	☐	☐	☐	☐	☐	☐
8	382/157; 382/158; 706/20; 706/31		Weidman, William E.	☒	☐	☐	☐	☐	☐	☐
9	382/157; 703/11; 706/20; 706/28; 706/31; 706/41		Weideman, William E.	☒	☐	☐	☐	☐	☐	☐
10	382/157; 706/20; 706/25; 706/30		Faggin, Federico et al.	☒	☐	☐	☐	☐	☐	☐

	Image D c. Displayed	PT
1	US 20030167148	☐
2	US 6198843	☐
3	US 6173275	☐
4	US 6092058	☐
5	US 6084981	☐
6	US 5465221	☐
7	US 5107442	☐
8	US 5075871	☐
9	US 4941122	☐
10	US 4802103	☐